Synergistic Effects of the Digital Economy on Common Prosperity in Rural China

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Abstract: *Under the strategic backdrop of rural revitalization, the digital economy has emerged as a pivotal engine for rural development in China. However, systematic research remains scarce on the ways in which synergistic effects of different emerging digital economic sectors influence rural income growth and distributional equality. This study focuses on the synergistic interaction between e-commerce and digital finance and examines their combined impact on rural income growth and distribution. Leveraging data from the E-commerce Demonstration Projects in Rural Areas and the Digital Inclusive Finance Index, our findings reveal: (1) synergistic effects significantly enhance farmers' income while reducing inequality metrics including the Gini coefficient and inter-quantile income gaps; (2) synergistic effects exhibit dynamic inclusivity, demonstrating more pronounced income-boosting effects in low-income counties (e.g. labor-intensive regions and financially underdeveloped areas); and (3) micro-mechanism analysis indicates that this synergy operates by stimulating local employment, simultaneously elevating wage-based and entrepreneurial incomes and narrowing disparities in entrepreneurial income. This research provides critical policy insights in terms of leveraging the digital economy in order to advance rural revitalization and prosperity.*

Keywords: *Digital economic synergy; Rural income distribution; Inclusive finance; Rural revitalization; Common prosperity*

JEL Classification Codes: O16; Q14; D31

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1. Introduction

Common prosperity is a central objective of China's economic and social development as well as a defining feature of Chinese modernization. The proposal for formulating the 14th Five-Year Plan, adopted at the Fifth Plenary Session of the 19th CPC Central Committee, sets the goal of achieving substantial progress toward common prosperity by 2035 and emphasizes consolidating poverty

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alleviation achievements and advancing rural revitalization. Furthermore, the Third Plenary Session of the 20th CPC Central Committee highlights the need to improve the institutions for supporting agriculture, benefiting farmers, and increasing rural prosperity, including expanding county-level income-generating industries and improving new rural industries and business models.

Despite China's historic achievements of lifting all rural residents out of poverty under the current standard and removing all 832 poverty-stricken counties from the poverty list by the end of 2020, the most challenging task in promoting common prosperity remains in rural areas, and rural development continues to be constrained by multiple structural factors. Traditional challenges such as low productivity and slow industrial upgrading remain unresolved, and regional income disparities have become increasingly pronounced (Ma, 2022). These disparities constrain the growth of rural consumption and may also weaken social equity and stability. Reducing the urban-rural divide therefore requires addressing income inequality within rural areas, which is essential for achieving the broader objective of common prosperity.

From a temporal perspective, China's progress toward common prosperity has coincided with the rapid expansion of the "digital economy". Between 2010 and 2020, rural digital infrastructure improved significantly, with internet penetration rising from 18.5% to 55.9%[1], laying a strong foundation for the digital economy's rural diffusion. In this context, e-commerce, digital finance, and other digital economic activities have expanded into rural areas at an accelerated pace, reducing search, evaluation, and monitoring costs associated with information asymmetry (Goldfarb and Catherine, 2019). As the most accessible digital tools for rural households, e-commerce and digital finance in particular have reshaped rural economies and created new momentum for productivity growth and high-quality development.

Despite this shared expansion, e-commerce and digital finance operate through distinct channels and play different roles in the rural economy. E-commerce platforms connect buyers and sellers by providing real-time market information and improving the matching of supply and demand. These features reduce information asymmetries in product markets and have reshaped traditional retail structures (Soh et al., 2006; Lendle et al., 2016). Digital finance, by contrast, refers to financial innovations enabled by digital technologies, with the primary goal of expanding access to financial services, especially for groups underserved by traditional financial institutions (Guo et al., 2020). Although both are part of the broader digital economy, e-commerce operates mainly through product-market transactions, and digital finance focuses on the provision of financial services.

The income effects of e-commerce are highly dependent on financial support. Rural e-commerce operators typically face binding liquidity constraints in areas such as upfront investment, marketing, and scaling production (Shao, 2017). The expansion of digital finance may help to ease these constraints and thereby amplify the income-generating effects of e-commerce. In addition, without concrete industrial application scenarios, the potential of digital finance to support rural development may not be fully realized. In the context of the digital economy, e-commerce provides such an application channel for digital finance. For example, Dangshan

[1] Source: China Internet Network Information Center (CNNIC).

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County in Anhui Province leveraged its fruit sector to promote pear sales through e-commerce, enabling more than 800 households to escape poverty. During peak seasons, interest-free loans provided by MYBank also helped merchants bridge liquidity gaps and expand their sales capacity, creating a reinforcing cycle linking industry, e-commerce, and finance[2]. Similar patterns have emerged in counties such as Wuchang in Heilongjiang, known for rice production, and Pingyang in Zhejiang, known for vermicelli and tomatoes, where rural e-commerce operators have also gained access to low- or zero-interest digital loans[3]. These cases suggest that the joint development of e-commerce and digital finance may generate substantial gains in household income.

Whether the interaction between e-commerce and digital finance can narrow income disparities and improve equality of opportunity (Fan, 2017) remains an open empirical question, however. This issue is central to rural development and the broader goal of common prosperity. Existing evidence shows that the risk of falling into a low-income trap is closely linked to individuals' initial opportunity endowments (Shi et al., 2022), suggesting that expanding development opportunities for low-income groups is critical for reducing inequality (Lin et al., 2023). In the digital era, data have become a key production factor, and the ability to access and process information, which is central to realizing the value of data, is increasingly shaping wealth distribution. Consequently, equality of opportunity in information access is becoming a critical dimension determining income disparities. E-commerce lowers information barriers in product markets and expands market-entry opportunities, and digital finance eases credit constraints and improves access to capital. Together, these forces may help reduce income gaps. Moreover, if the benefits of digital technologies accrue disproportionately to higher-income groups, they may reinforce a Matthew effect and widen rural income inequality. Whether the synergy between e-commerce and digital finance ultimately promotes common prosperity or exacerbates inequality therefore remains an empirical question, one with important implications for the design of rural digital-economy policies.

This study contributes to the existing literature in three important ways. First, it offers a novel examination of the synergistic effects between e-commerce and digital finance, two forms of digital economic activity most widely used by rural households, on both income levels and income distribution. The analysis highlights how different digital technologies may reinforce or offset one another. Existing studies typically investigate these activities in isolation (Zhang et al., 2019; Tang et al., 2020). By contrast, to our knowledge, this paper provides the first systematic integration of e-commerce, digital finance, and income inequality within a unified analytical framework, thereby addressing a notable gap in the literature on digital-economy synergies.

Second, we use recentered influence function (RIF) regressions to study how e-commerce and digital finance affect the entire rural income distribution. This distributional perspective offers a novel way to think about the digital divide. Compared to subsample analysis (Zeng et al., 2018; Zhang et al., 2019) or quantile regressions (Qiu and Zhou, 2021), our approach directly

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[2] Source: "Dangshan Pears and Other County-Level Specialty Industries Receive Interest-Free Loans from MYBank," https://baijiahao.baidu.com/s?id=1703444027483828597&wfr=spider&for=pc.

[3] Source: "Supporting Rural Industrial Revitalization! MYbank Offers Interest-Free Loans to 100 Leading Agricultural Counties, First Implemented in Zhejiang," https://baijiahao.baidu.com/s?id=1733243491635251017&wfr=spider&for=pc.

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decomposes standard inequality measures, providing a clearer and more policy-relevant picture of how digital development reshapes rural incomes.

Finally, to our knowledge, the paper advances the literature by combining decomposition techniques with heterogeneity analysis to offer the first systematic assessment of how changes in digital-economy activities relate to the evolution of inequality measures. The examination of cross-county and labor-income heterogeneity allows for a more granular characterization of distributional dynamics and offers mechanism-based insights that reinforce the RIF regression results, thereby strengthening the policy relevance of the findings.

The remainder of the paper is organized as follows. Section 2 reviews the literature on e-commerce, digital finance, and income inequality. Section 3 develops the theoretical framework. Section 4 describes the empirical strategy. Section 5 presents the empirical results, and Section 6 concludes with a discussion of policy implications.

2. Literature Review

To describe regional income disparities, we rank provinces separately by per capita disposable income for urban and rural residents and derive the ratio of the five highest-income provinces to the five lowest-income provinces. This yields measures of inequality within urban areas and within rural areas. We also use the national ratio of urban to rural disposable income to capture the overall urban-rural gap. As shown in Figure 1, inequality within rural areas has declined over time but remains substantially larger than inequality within urban areas. In 2020, the within-rural income ratio was 2.43, compared to 1.89 for within-urban ratio, and surpassing the national urban-rural ratio of 2.37. These figures indicate that income inequality within rural areas deserves greater attention. Against this background, we examine how the digital economy influences rural common prosperity by focusing on changes in both the level and the distribution of rural income.

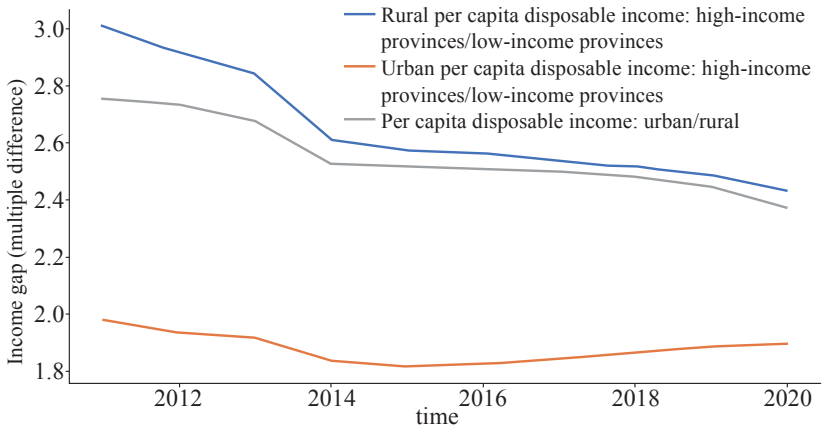

Fig. 1. Urban–Rural Income Gap, Within-Urban Inequality, and Within-Rural Inequality

Source: National Bureau of Statistics of China (www.stats.gov.cn), which provides the China Statistical Yearbook and access to compiled national and regional statistics, available for online query and download.

A large body of research has examined changes in farmers' income by focusing on individual characteristics and regional conditions, providing the theoretical basis for this study. On the individual side, most work highlights the role of human capital, especially education and health.

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On the regional side, economic conditions receive the most attention, with infrastructure and access to finance seen as the two key factors. Studies show that rural infrastructure tends to raise farmers' income both within a province and in neighboring provinces, and the gains are stronger in areas with lower levels of human capital (Luo and Fan, 2012). Rural finance is a major topic in this literature. Because financial institutions often favor wealthier clients, China's rural financial system has long underperformed and exhibits clear signs of financial exclusion (Dong and Xu, 2012). Two main mechanisms are often discussed. The first is geographic exclusion. Establishing financial outlets in remote areas is costly, which limits farmers' access to financial services (Leyshon and Thrift, 1996). The second is assessment exclusion. Due to information asymmetry in credit markets, lenders worry about default risk and are reluctant to extend loans (Meyer, 1998).

Beyond these traditional factors, recent studies have begun to incorporate e-commerce and digital finance, the two forms of digital activity that rural households interact with most frequently.

For e-commerce, the literature generally finds that it plays an important role in reducing information asymmetry, lowering search costs, and decreasing price dispersion (Jensen, 2007; Roberts et al., 2017). Empirical studies also show that the expansion of e-commerce tends to raise rural household income (Zeng et al., 2018; Tang et al., 2020; Qiu and Zhou, 2021). Whether its growth affects income inequality is less clear. Existing work typically examines two dimensions: urban-rural differences and inequality within rural areas, but the conclusions are mixed. Some scholars argue that the effectiveness of digital technologies depends heavily on education (Ono and Zavodny, 2007). Because urban residents generally have higher educational attainment than rural residents, they may benefit more from the rise of e-commerce (Zhang and Han, 2017), which could widen the urban-rural income gap. Others hold the opposite view, suggesting that e-commerce reduces the "digital divide" between urban and rural areas, promotes the movement of capital and labor, and thereby narrows the income gap (Chen et al., 2021). For inequality within rural areas, one line of research notes that rural e-commerce producers differ widely in their initial levels of physical capital (Zeng et al., 2018). As these differences translate into differences in "internet capital", income disparities may widen (Qiu et al., 2016). A different set of studies, however, argues that e-commerce improves "equality of market access" by lowering entry barriers, which helps narrow income gaps among rural households (Qiu and Zhou, 2021).

For digital finance, the current literature views it as a form of finance that retains core functions of payments, investment, and credit (Guo et al., 2020), while also being more inclusive. Online lending connects borrowers and lenders across long distances, helping overcome geographic barriers to financial access. Big-data-based credit assessment allows financial institutions to combine scattered information and evaluate borrowers more effectively, reducing assessment barriers as well. Empirical studies have shown that digital finance reduces demand for formal productive credit in rural areas and complements traditional financial services (Fu and Huang, 2018). It also relaxes farmers' financing constraints, improves entrepreneurial performance (He and Li, 2019), and raises rural household income (Zhang et al., 2019). A growing literature has also examined how digital finance affects the urban-rural gap and inequality within rural areas. Most studies find that digital inclusive finance helps narrow the income gap between urban and rural residents (Yang et al., 2022). Evidence on whether it widens inequality within rural areas,

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however, remains mixed. One view argues that digital finance may generate a Matthew effect (Wang and Zhao, 2020), reflected in larger differences in wage and business income between poor and non-poor households. Another emphasizes its inclusive nature, showing that digital finance improves rural entrepreneurship and broadens access to business opportunities, which can raise the incomes of low-income households and support more inclusive growth (Zhang et al., 2019; Feng and Zhang, 2024).

Some studies also examine the relationship between these two digital activities and their potential synergies. Kang et al. (2018) were among the first to outline how "rural e-commerce and inclusive finance" can support targeted poverty alleviation and proposed related policy measures. Similarly, Zhou et al. (2023) provide empirical evidence that digital finance strengthens the income-enhancing effects of e-commerce for rural households, and Fang et al. (2024) further show that digital finance can help offset the inequality effects that may arise from e-commerce development. Although these studies examine the potential effect of synergy between e-commerce and digital finance, they do not investigate how their joint development affects the overall income distribution, particularly income inequality, nor do they explore the mechanisms behind these effects.

In summary, most studies of the digital economy focus on the income and distributional effects of a single digital activity. Much less is known about how different digital services interact and what their combined effects imply for rural common prosperity. Evidence on inequality is also mixed, partly because studies adopt different definitions, such as the urban-rural gap or group-based disparities, and partly because varied samples and methods. As a result, relatively few papers examine changes across the full income distribution. To fill these gaps, in this paper we use inequality decomposition to assess whether the joint development of e-commerce and digital finance has contributed to advancing common prosperity in rural China.

3. Theoretical Framework

This section develops a theoretical model to illustrate how the interaction between e-commerce and digital finance can influence rural household income. Consider a perfectly competitive product market in which neither excess supply nor excess demand arises in equilibrium. Because the empirical analysis relies on region-level measures of e-commerce and digital finance, the model treats each region as having a single representative farmer-producer. For simplicity, we abstract from labor-market exit and unemployment. The basic setup is as follows.

At the beginning of the period, the representative farmer chooses either wage employment or production. If the farmer works for wages, one unit of labor earns a fixed payment w at the end of the period. If the farmer chooses production, income depends on the output y produced and the local market price p with the farmer taking the price as given. Output is determined by the following production function:

$$y=k^{\alpha} \tag{1}$$

Let k denote the farmer's capital input per unit of labor, and let α be the output elasticity of capital, where $0<\alpha<10$. The farmer is endowed with physical capital z, which can be used to purchase productive inputs. Following Evans and Jovanovic (1989) and Bianchi (2010), we assume that financial institutions provide savings and credit services. The farmer can either deposit funds

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at the financial institution and earn interest or borrow from it. Let the market interest rate be $r-1$ so that a deposit of z yields a gross return of rz at the end of the period. If the farmer chooses to borrow, the available loan amount is proportional to the farmer's physical capital. The credit limit is $(\lambda-1)z$, where λ is the leverage multiplier. We relax the common assumption that λ is constant and instead allow it to vary with the monitoring and evaluation costs c_1 to capture the changes in local financial conditions:

$$\lambda=\lambda(c_1) \tag{2}$$

We assume $\lambda'(c_1)<0$, which implies that higher monitoring and evaluation costs make lenders more cautious. In other words, when financial institutions worry about ex post risk, they prefer borrowers with stronger collateral positions and better credit records. This assumption reflects the problem of limited financial access in rural China due to assessment-based credit exclusion. The farmer can invest at most $\lambda(c_1)z$ units of capital in production, that is $0\leq k\leq\lambda(c_1)z$. If the farmer chooses production, the net profit is:

$$profit=py+r(z-k) \tag{3}$$

The farmer chooses the level of capital input that maximizes net profit given the physical capital endowment and the financing constraint. The optimization is thus:

$$\max_k pk^{\alpha}+r(z-k) \qquad s.t. \qquad 0\leq k\leq\lambda(c_1)z \tag{4}$$

If the farmer's physical capital endowment plus available credit is insufficient to reach the optimal level of capital input, the farmer becomes credit constrained. Ignoring the financing constraint for the moment, the unconstrained optimal solution to equation (4) is:

$$k^{*}=\left(\frac{p\alpha}{r}\right)^{\frac{1}{1-\alpha}} \tag{5}$$

Thus, when the farmer is not constrained by the credit, the optimal capital input is k^{*}, which satisfies $0\leq k^{*}\leq\lambda(c_1)z$. For a credit-constrained farmer, the optimal choice is instead $\lambda(c_1)z$. Simplifying the condition $0\leq k^{*}\leq\lambda(c_1)z$, the farmer is thus unconstrained if and only if:

$$p\leq\frac{[\lambda(c_1)z]^{1-\alpha}r}{\alpha} \tag{6}$$

Overall, for a given output price, the farmer's maximum profit from producing the specialty product is:

$$profit=\begin{cases} p^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}}+r\left[z-\left(\frac{p\alpha}{r}\right)^{\frac{1}{1-\alpha}}\right] & \text{if unconstrained,} \\ p[\lambda(c_1)z]^{\alpha}+r[z-\lambda(c_1)z] & \text{if constrained.} \end{cases} \tag{7}$$

A farmer chooses production if and only if $profit\geq w+rz$. Otherwise he chooses wage employment. Using equation (7), we can determine the farmer's decision, given the output price, initial capital endowment, and whether the farmer is credit constrained.

A farmer who chooses to produce and is not credit constrained satisfies the following condition:

$$p^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}}-r\left(\frac{p\alpha}{r}\right)^{\frac{1}{1-\alpha}}\geq w \text{ and } p\leq\frac{[\lambda(c_1)z]^{1-\alpha}r}{\alpha} \tag{8}$$

and a farmer who chooses to produce and is credit constrained satisfies the following condition:

$$p[\lambda(c_1)z]^{\alpha}-r\lambda(c_1)z\geq w \text{ and } p>\frac{[\lambda(c_1)z]^{1-\alpha}r}{\alpha} \tag{9}$$

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Using equations (8) and (9), we obtain the following interpretation. When the output price is very low, all farmers prefer wage employment to production. As the price rises, production eventually becomes more profitable than wage work. However, for a given leverage multiplier, only farmers with sufficiently high physical capital can borrow enough to reach the optimal level of capital input and earn the unconstrained profit. For farmers who are credit constrained, the maximum profit they can achieve depends on their own capital endowment. When their physical capital and the amount of credit they can obtain are too low, even a higher output price does not make production more attractive than wage employment for them.

The above analysis takes the price as given, but the market conditions may also change. To link e-commerce and digital finance within our theoretical framework, we relax the assumption of a fixed sales price and allow e-commerce development to affect the price farmers can obtain. We incorporate a search model to examine how the feasible local selling price varies with the extent of e-commerce. Following the price-searching framework in Aker (2008) and Xu et al. (2013), farmers must search the product market to find a suitable selling price. Let $H(p)$ denote the distribution of offline prices across different regions, with density $h(p)$ on the support $p\in[p_{min},p_{max}]$. Suppose a farmer has produced x units of output and has a best known selling price p_n. By paying a search cost c_2 per attempt, the farmer draws a new potential price p. If $p>p_n$, the farmer sells at p. Otherwise, the product is sold at the original price p_n. The expected net return from the search is:

$$gain=\int_{p_n}^{p_{max}}(p-p_n)xh(p)dp-c_2x=x\int_{p_n}^{p_{max}}ph(p)dp-p_nx\left[1-H(p_n)\right]-c_2x \qquad (10)$$

If $gain\leq 0$, the farmer chooses not to search. If the gain is positive, the farmer continues searching until finding a price that yields a higher net profit than the profit associated with the current best price. Let p^* denote the optimal selling price. In equilibrium, the marginal improvement from conducting one more search is zero. Thus, we have:

$$x\int_{p^*}^{p_{max}}ph(p)dp-p^*x\left[1-H(p^*)\right]-c_2x=0 \qquad (11)$$

Taking the derivative of equation (11), we obtain:

$$\frac{\partial p^*}{\partial c_2}=\frac{1}{H(p^*)-1}<0 \qquad (12)$$

This equation implies that a decline in search costs raises the farmer's optimal selling price. The intuition is that geographic and informational frictions segment local markets and create potential arbitrage opportunities across regions. When search costs fall, farmers gain better access to price information, allowing them to take advantage of these opportunities and secure higher selling prices (Jensen, 2007; Xu et al., 2013)[4].

[4] The development of e-commerce improves the matching of buyers and sellers and reduces the market power of intermediaries (Xu et al., 2013). As a result, producers receive higher selling prices, and consumers face lower purchase prices. The simultaneous increase in producer and consumer surplus is not contradictory. Both arise from a reduction in the surplus captured by intermediaries. This pattern is consistent with current e-commerce practices. For example, after pineapples in Xuwen, Guangdong began to be sold directly through online platforms, the farmgate price rose rather than fell (source: http://www.zgxwzk.chinanews.com.cn/observe/2024-03-04/21354.shtml). Since this study focuses on farmers' income, the theoretical analysis focuses on the producer price.

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Figure 2 shows how farmers' production decisions vary with the selling price and their capital endowment. In the left panel, the horizontal axis represents the farmer's physical capital endowment and the vertical axis represents the selling price. The upward-sloping curve is the financing-constraint line, derived by setting equation (6) to equality. Farmers located to the left of this line are unconstrained, and those to the right face a binding credit constraint. The curve that slopes downward and then becomes horizontal is the indifference curve between wage work and production, obtained by setting the first condition in equations (8) and (9) to equality. Farmers located to the left of this curve choose wage employment, and those to the right choose production and earn strictly higher profits than the wage they could receive. When the price is low, all farmers lie to the left of the indifference curve, making wage work more attractive than production. According to equation (12), as e-commerce expands and search costs fall, the selling price rises. Once the price reaches a sufficiently high level, farmers with capital endowments to the right of point A choose production. Among them, those between points A and B face a binding credit constraint because their endowment and available borrowing are not enough to reach the optimal scale. Farmers to the right of point B are not credit constrained.

As the price continues to rise, the size of the product market expands and more farmers choose to produce, but a larger share of them also become credit constrained. A higher price increases the potential return to production, inducing some farmers who previously preferred wage work switch to production. These farmers, located between points C and A, have relatively low capital endowments and therefore cannot reach the profit-maximizing scale. Farmers who were previously unconstrained may now want to expand production as the potential profit rises. Their optimal capital input increases, and some of them may again hit the credit constraint, between points B and D.

The expansion of digital finance reduces monitoring and evaluation costs, allowing farmers to obtain more credit. As the leverage multiplier increases, both the indifference curve and the financing-constraint line shift leftward (Figure 2 right panel). Farmers with relatively high capital endowments who were previously credit constrained can now reach the optimal level of capital input, located between points F and D. Farmers with lower capital endowments also become more likely to choose production once additional credit becomes available. Although they still cannot achieve the unconstrained optimum, they can invest more capital and earn higher profits, located between points E and C. For those who remain constrained (between points C and F), digital finance still supplements their capital input and raises their production profit.

Combining equations (2), (7), and (12), we obtain:

$$\frac{\partial profit}{\partial c_1}>0;\ \frac{\partial profit}{\partial c_2}>0;\ \frac{\partial profit}{\partial c_1 \partial c_2}>0 \tag{13}$$

Increases in digital finance, e-commerce, and their interaction thus all raise farmers' income. Based on equation (13), we estimate a panel-data model that includes an interaction term between e-commerce and digital finance to test these predictions empirically.

Achieving common prosperity in rural areas requires both income growth and a reduction in income disparities. Equation (7) implies that the effects of e-commerce and digital finance vary with farmers' capital endowments. Farmers without binding credit constraints benefit from market expansion under e-commerce through higher optimal profits. Credit-constrained farmers, by

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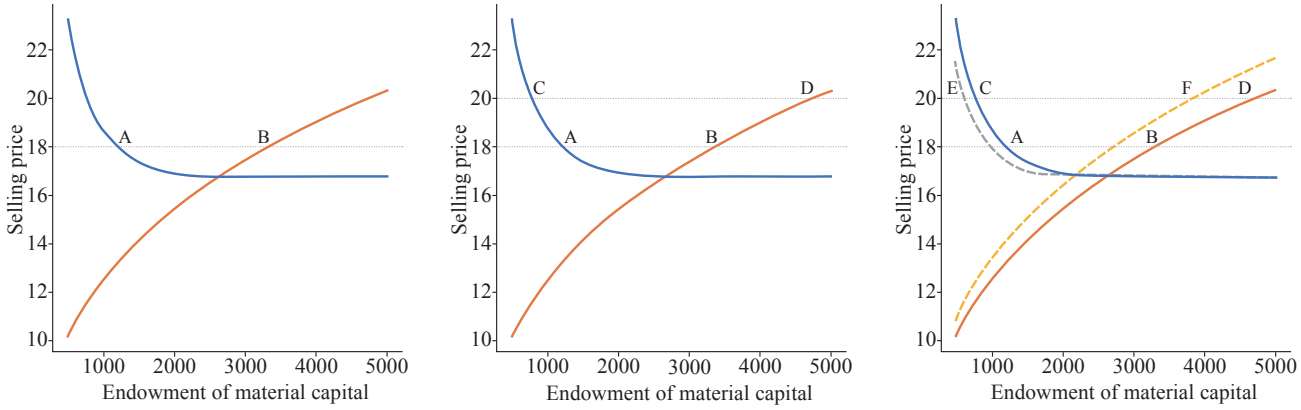

Fig.2. E-Commerce, Digital Finance, and Production Decisions[5]

contrast, gain when e-commerce and digital finance jointly relax borrowing limits and raise selling prices. Some farmers who previously relied on wage employment may also shift toward production as returns increase and access to credit improves. These channels have opposing implications for inequality: higher-capital farmers may experience larger income gains, and lower-capital farmers benefit from eased constraints and improved profitability. Whether these gains are sufficient to reduce overall income inequality is therefore an empirical question.

4. Empirical Strategy

In this section, we empirically examine whether the interaction between e-commerce and digital finance increases farmers' income or affects income inequality. Specifically, we use the E-Commerce in Rural Areas Comprehensive Demonstration Program as a quasi-natural experiment to capture exogenous variation in e-commerce development[6]. The E-Commerce in Rural Areas Demonstration Program is a county-level initiative launched by the Ministry of Finance and the Ministry of Commerce to accelerate the development of rural e-commerce. Its first cohort of pilot counties was announced in 2014, and new cohorts have been added each year since then. Each pilot county receives approximately 20 million RMB in funding, which is used for five main components: service site construction, operations centers, logistics infrastructure, brand promotion, and e-commerce training. A review of policy documents indicates that no other policies overlap with the timing or location of the pilot program during our sample period, nor have we identified policies with similar functions.[7] Existing studies have found that the pilot program raises per capita net income in rural areas and reduces poverty (Tang et al., 2020; Zhou et al., 2023).

For digital finance, we follow the literature and use the Peking University Digital Inclusive

[5] This figure presents results from a numerical simulation. The model parameters were set as follows: w=150, α=0.7, r=1.02. The leverage multiplier λ increased from 1.3 to 1.6, and the selling price p increased from 18 to 20.

[6] We refer to this program as the "pilot county policy", and counties selected into the program as "pilot counties".

[7] During the sample period, the Ministry of Agriculture promoted and implemented the "Information-to-Villages and Households" project, which aimed to achieve full network coverage across the province and enable ordinary farming households to access convenient and efficient information services without leaving their villages or homes. Therefore, this paper includes it as one of the control variables to exclude the impact of rural internet infrastructure improvements on farmers' income.

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Finance Index, which compiled by the Institute of Digital Finance at Peking University in collaboration with Ant Group, to measure the degree of regional digital finance development (Zhang et al., 2019; Guo et al., 2020).

4.1 Data Sources

The "Peking University Digital Inclusive Finance Index" is available at the county level for 2014-2018, and the China Family Panel Studies (CFPS) also provide data for these years. For consistency, our analysis therefore focuses on this period exclusively. County-level digital finance data come from the Open Research Platform for the Digital Economy.

The list of pilot counties for the e-commerce into Rural Areas program was obtained from the Ministry of Commerce. County-level socioeconomic characteristics are drawn from the China County Statistical Yearbook and the EPS database, and micro-level information is derived from the CFPS. County-level data were used to establish the main results, conduct robustness checks, and examine the mechanisms through which the interaction between e-commerce and digital finance affects rural common prosperity. Micro-level survey data are then used to explore the underlying mechanisms from the perspective of rural households.

4.2 Variable Definition

4.2.1 Dependent variables

To examine how the interaction between digital economic activities impacts common prosperity in China's rural areas, we focus on changes in the distribution of income. The dependent variable (*lninc*) is the logarithm of rural per capita disposable income at the county level. The data are sourced from the *China County Statistical Yearbook,* counties with missing values are excluded from the analysis.

4.2.2 Independent variables

E-commerce pilot policy (ec_{cpt}). This variable equals 1 if county *c* in province *p* is designated as a pilot county in year *t*, and 0 otherwise. Our analysis covers 1,521 counties, of which 721 were designated as pilot counties at some point during the sample period. Digital finance development(df_{cpt}). This variable measures the level of digital finance development in county *c* of province *p* in year *t*. To examine the mechanisms involved, we consider several dimensions of digital finance, including coverage, usage, and credit. For comparability with income and inequality measures, all digital finance indices are divided by 100, and observations with missing values are excluded.

4.2.3 Control variables

The empirical model incorporates several county-level controls that may influence farmers' income. Economic development is measured by the logarithm of per capita GDP (*lngdp*). Agricultural machinery (*mach*) is defined as the total power of agricultural machinery in millions of kilowatts. We also control for the structure of the local economy, including the shares of primary (*agri*) and secondary (*indust*) industries in GDP. The composition of the labor force is captured by the share of rural employment in total employment (*labrural*) and the share of agricultural employment in rural employment (*labfarm*). Fiscal expenditure (*fis*) is measured as

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local government general budget spending relative to GDP, and traditional finance (*tfin*) is defined as the ratio of outstanding loans at year-end to GDP. To account for information access, we include the logarithm of fixed-line telephone users (*lntel*) and a dummy variable for participation in the Information into Villages and Households program (*info*).

4.2.4 Micro-level variables

To explore the underlying mechanisms inherent in our model, we examine two channels: labor income and labor allocation. For labor income, we focus on changes across different income sources. Rural household income is divided into wage income and self-employment income, with the latter including both agricultural and nonagricultural self-employment earnings. We take the logarithm of each income category (denoted as *lnincwage* and *lnincope*) as the dependent variables. For labor allocation, we study whether the spatial distribution of labor is affected by the development of digital economic activities and their interaction. The number of household members working locally (*joblocal*) serves as the dependent variable. The key independent variables are defined as in the county-level analysis, and we also include several micro-level controls including household size (*size*), measured as the number of permanent household members; household labor force share (*labor*), defined as the ratio of labor force members to household size; male share (*gender*), the proportion of male workers in the household labor force; health status (*health*), the share of workers reporting fair or better health; and years of schooling (*eduy*), the average educational attainment of household labor force members. Observations with missing or abnormal values in the control variables were dropped, so the final dataset is an unbalanced panel of households observed in two survey years.

4.3 Empirical Mode

The empirical analysis focuses on whether the interaction between e-commerce and digital finance promotes common prosperity by altering the distribution of farmers' income. We first examine the relationship between income and these two digital economic activities using the following specification:

$$lninc_{cpt}=\beta_1 ec_{cpt}+\beta_2 df_{cpt}+\beta_3 ec_{cpt}\times df_{cpt}+\gamma x_{cpt}+\alpha_c+\delta_t+\theta_{pt}+\epsilon_{cpt} \quad (14)$$

The specification follows the difference-in-differences framework to identify the impact of the pilot county policy on farmers' income and also incorporates the digital finance index and its interaction with the policy. Subscripts c, p, and t denote county, province, and year, respectively. x is a vector of control variables. County fixed effects α_c absorb time-invariant unobserved characteristics affecting income. Year fixed effects δ_t capture common time shocks, and province-year fixed effects θ_{pt} control for macroeconomic changes that vary across provinces over time. ϵ_{cpt} is the error term. The coefficient on the interaction term (β_3) measures how the income effect of the pilot policy varies with the level of digital finance development.

To examine the impact on income inequality, we estimate an analogous specification:

$$RIF(inc;v,F)_{cpt}=\beta_1 ec_{cpt}+\beta_2 df_{cpt}+\beta_3 ec_{cpt}\times df_{cpt}+\gamma x_{cpt}+\alpha_c+\delta_t+\theta_{pt}+\epsilon_{cpt} \quad (15)$$

Equation (15) is the recentered influence function regression. The dependent variable $RIF(inc;v,F)$ represents the recentered influence function of distributional statistic v for rural per capita disposable income inc, where inc follows distribution F. In the empirical analysis, we focus

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on three commonly used measures of dispersion: the Gini coefficient (*gini*), the 90-10 percentile ratio (*range*), and the variance (*var*). The construction of the RIF terms follows Firpo et al. (2018).

Measures of income inequality are fundamentally distributional statistics, and our goal is to examine whether the interaction between e-commerce and digital finance affects the unconditional income distribution of rural households. Firpo et al. (2009) introduced the recentered influence function (RIF) as a way to estimate the partial effects of explanatory variables on distributional statistics within a regression framework, and this approach is well suited to our analysis of income disparities. To clarify how RIF regression is used in this study, we briefly outline its key steps:

Let the dependent variable Y follow the original distribution F_Y, and let F_y denote the degenerate distribution that places all mass at y. The influence function (IF) of a distributional statistic $v(F_Y)$ evaluated at $Y=y$ is defined as:

$$IF(y;v,F)=\lim_{h\downarrow 0}\frac{v\left[(1-h)F_Y+hF_y\right]-v(F_Y)}{h} \tag{16}$$

The function captures how the distributional statistic changes when the mass at $Y=y$ is increased by an infinitesimal amount. Thus, for a given original distribution and statistic, the influence function is a function of the sample value y. The recentered influence function is then defined as the influence function plus the original statistic:

$$RIF(y;v,F)=IF(y;v,F)+v(F_Y) \tag{17}$$

Because the influence function has a zero mean, the expected value of the RIF equals the distributional statistic itself:

$$E[RIF(y;v,F)]=\int[IF(y;v,F)+v(F_Y)]dF_Y(y)=v(F_Y) \tag{18}$$

Using county-level data from the China County Statistical Yearbook, we construct the RIF for rural per capita income. Taking the conditional expectation of both sides of equation (15) yields:

$$E[RIF(inc;v,F)/W=w]=\beta_1 ec+\beta_2 df+\beta_3 ec\times df+\gamma x+\alpha+\delta+\theta \tag{19}$$

On the left-hand side, W denotes all explanatory variables in the model. By property (18), the expected value of the RIF for county-level rural income equals the national distributional statistic of rural per capita disposable income. That is, the left-hand side of equation (19) equals $v(F_{inc})$. Thus, equation (15) can be used to examine how e-commerce, digital finance, and their interaction affect income inequality across rural China. The estimated coefficients reflect the partial effects of each variable on the inequality measure. For example, when the Gini coefficient is used as the distributional statistic, β_1, β_2 capture the effects of the e-commerce pilot policy and digital finance on the Gini coefficient calculated from county-level income, while β_3 measures their interaction effect.

In summary, the use of RIF regression offers several advantages[8]. First, it captures how digital economic activities shape the overall income distribution, making it well aligned with the policy

[8] It is important to note that RIF regression also has limitations. First, its validity relies on the regularity condition in equation (18) (Firpo et al., 2009; Firpo et al., 2018), which requires a sufficiently large sample. With 1,521 counties in our dataset, this condition is reasonably satisfied. Second, because RIF regression is fundamentally a statistical rather than causal method, it cannot fully rule out endogeneity or omitted-variable bias (Heckley et al., 2016). To address these concerns, we complement the RIF regressions with instrumental-variable estimation, the Heckman two-step procedure, and Chamberlain's correlated random-effects approach to mitigate endogeneity and sample-selection issues.

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goal of common prosperity, which concerns both rising mean income and reduced dispersion rather than outcomes for specific subgroups. Second, because RIF regression remains within the OLS framework, the coefficients are straightforward to interpret. Equation (19) shows that the distributional statistic can be written as a linear projection on the explanatory variables, unlike quantile regression, whose coefficients have a different interpretation. Finally, RIF regression has a clear theoretical foundation and is empirically simple to implement, and it is compatible with two-way fixed-effects estimation (TWFE).

5. Empirical Results

5.1 Baseline Results

Table 1 reports the main estimates. The coefficient on the interaction between the pilot county policy and the overall digital finance index is 0.0258. This implies that for every 100 unit increase in the digital finance index, the income effect of the e-commerce pilot program rose by 2.58%, a magnitude that is economically meaningful. At the sample mean of the digital finance index, the policy effect is 3.39%, close to the estimate in Tang et al. (2020). In counties with the lowest level of digital finance, the policy effect was only 1.60%, whereas in counties with the highest level it reached 4.69%. Across different dimensions of digital finance, both the overall index and the coverage index are positively and significantly associated with farmers' income. The usage and credit indices also enter with positive signs, though the coefficients are not statistically significant. Regardless of the dimension considered, the interaction between the pilot program and digital finance was consistently positive and significant. A plausible explanation is that the credit-enhancing role of digital finance operated most effectively when embedded in concrete application scenarios such as e-commerce.

TABLE 1. Synergistic Effects of E-Commerce and Digital Finance on Farmers' Income

Dependent variable: Farmers' income	Digital finance index dimension			
	(1) Overall index	(2) Coverage	(3) Usage	(4) Credit
Pilot county policy	0.0128*** (0.00160)	0.0132*** (0.00160)	0.0147*** (0.00160)	0.0143*** (0.00159)
Digital finance index	0.0646*** (0.00743)	0.0494*** (0.00497)	0.00722 (0.00854)	0.00138 (0.00492)
Pilot county × Digital finance	0.0258*** (0.00575)	0.0203*** (0.00685)	0.0167*** (0.00406)	0.0169*** (0.00348)
Observations	7117	7117	7117	7117

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors clustered at the county level are reported in parentheses. All regressions control for the full set of covariates as well as county, year, and province-by-year fixed effects.

In the empirical analysis, income inequality was measured using the Gini coefficient, the 90-10 percentile ratio, and the variance. Table 2 reports the estimates from equation (15). In Panel A, column (1), the interaction between the pilot county policy and the digital finance index is negative, indicating that the inequality-reducing effect of the pilot policy became stronger as digital finance

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developed. For example, at the minimum value of the digital finance index, the policy reduced the Gini coefficient by 0.058. At the maximum value, the reduction increased to 0.170. The different components of digital finance exhibit heterogeneous effects, however. Across all three inequality measures, improvements in coverage showed the strongest association with reduced inequality, whereas usage depth had a weaker impact. Although digital credit was positively correlated with inequality, its interaction with the pilot policy was negative. Taken together, the results in Tables 1 and 2 indicate that digital finance advances rural common prosperity more effectively when it is coupled with concrete application scenarios such as e-commerce.

TABLE 2. Synergistic Effects of E-Commerce and Digital Finance on Rural Income Inequality

	Digital finance index dimension			
	(1) Overall Index	(2) Coverage	(3) Usage	(4) Credit
Panel A: Dependent variable: RIF(*inc; gini*)				
Pilot county policy	-0.0465*** (0.00327)	-0.0482*** (0.00330)	-0.0557*** (0.00341)	-0.0539*** (0.00338)
Digital finance index	-0.352*** (0.0190)	-0.251*** (0.0132)	-0.0532*** (0.0184)	0.0308*** (0.0115)
Pilot county × Digital finance	-0.0938*** (0.0170)	-0.0639*** (0.0163)	-0.0651*** (0.0126)	-0.0621*** (0.0109)
Panel B: Dependent variable: RIF(*lninc; range*)				
Pilot county policy	-0.259*** (0.0327)	-0.269*** (0.0327)	-0.316*** (0.0326)	-0.311*** (0.0325)
Digital finance index	-1.990*** (0.168)	-1.383*** (0.110)	-0.310* (0.175)	0.124 (0.111)
Pilot county × Digital finance	-0.603*** (0.130)	-0.497*** (0.153)	-0.391*** (0.0919)	-0.337*** (0.0794)
Panel C: Dependent variable: RIF(*lninc; var*)				
Pilot county policy	-0.0661*** (0.00487)	-0.0674*** (0.00486)	-0.0793*** (0.00518)	-0.0774*** (0.00516)
Digital finance index	-0.486*** (0.0254)	-0.344*** (0.0174)	-0.0976*** (0.0283)	0.0201 (0.0189)
Pilot county × Digital finance	-0.104*** (0.0202)	-0.0692*** (0.0224)	-0.0660*** (0.0141)	-0.0641*** (0.0121)
Observations	7117	7117	7117	7117

Note:*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors clustered at the county level are reported in parentheses. All regressions include the full set of controls as well as county fixed effects, year fixed effects, and province-by-year fixed effects.

5.2 Robustness Checks

Given that our empirical strategy relies on two key explanatory variables: the e-commerce demonstration county policy and the digital financial inclusion index, we also conduct a series of robustness checks. We begin by examining the robustness of the policy effect and then proceeded to treat the policy as an external shock to address potential endogeneity concerns related to the digital finance index. Finally, we re-estimate the model using alternative data sources and variable definitions.

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5.2.1 Robustness of the policy effect

The validity of the original difference-in-differences approach used relies on the parallel trends assumption. That is, farmers' income in the treated and control counties followed similar trends prior to the policy. Following Beck et al. (2010), we construct a set of event-time indicators *ec_k*(*k*=-3, -2, 0, 1, 2, 3, 4), where each indicator equals one if a county was designated as an E-commerce into Rural Areas Demonstration county *k* years earlier. The estimation results show that the coefficients on *ec_*-3 and *ec_*-2 are statistically indistinguishable from zero, supporting the parallel trends assumption. After the policy was implemented, the coefficients became significantly positive and increased over time. Second, recent studies note that estimating staggered policy adoption using a two-way fixed effects (TWFE) model may yield biased estimates (Goodman-Bacon, 2021). To address this concern, we re-estimated the income effects of the demonstration policy using a staggered difference-in-differences approach. Although the estimates differ somewhat from those obtained under TWFE, the bias appears to be downward. This suggests that the true policy effect is likely larger than our baseline estimates, indicating that the TWFE results are conservative and thus robust. Third, because some demonstration counties are designated poverty counties, estimates based on the full sample may partly capture the effects of other national poverty-alleviation programs. After excluding poverty counties from the sample, we re-estimated the model and found that the demonstration policy continues to increase county-level farmers' income significantly.

5.2.2 Endogeneity of the digital finance index

To address potential endogeneity, we exploit the time-varying nature of digital inclusive finance and the differential trends across its sub-indices. Specifically, we construct instruments by interacting the logarithm of the distance from each county to Hangzhou with the annual mean of each sub-index ($lndist_c \times \overline{df}_t$). We further interact these instruments with the policy indicator to instrument the interaction between digital finance and the demonstration-county policy. Compared to the baseline results in Table 1, the estimated complementarity between digital finance and the policy is stronger. Fixed-effects estimates understate the interaction effect, and the IV approach corrects for this bias. The Kleibergen-Paap rk Wald F statistics exceed conventional thresholds, alleviating concerns about weak instruments. Moreover, residuals from regressing farmers' income on digital finance, the policy indicator, and controls are uncorrelated with the instruments, supporting their exogeneity. Because the RIF regressions are also based on farmers' income, similar endogeneity concerns may arise. Applying the same IV strategy to the RIF framework yielded results consistent with those in Table 2.

5.2.3 Other robustness checks

First, using household-level microdata, we estimated Equations (14) and (15) with annual household net income as the dependent variable, and the results are consistent with those reported in Tables 1 and 2. Second, we estimated Equation (14) using the county-level urban–rural income gap ($lninc_{urban}$ -$lninc_{rural}$) as the outcome variable and found that the interaction between e-commerce and digital finance significantly narrowed the urban-rural income gap. Finally, we applied RIF regressions to the mean of farmers' income. The results closely mirror those from the

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baseline estimation of Equation (14) in Table 1, supporting both the reliability of the RIF approach for decomposing distributional statistics and the robustness of our baseline findings.

5.3 Further Analy

5.3.1 Decomposition of changes in inequality measures

Policymakers are often more concerned with how income inequality evolves over time than with its level at any given point in time. Over our sample period, the Gini coefficient of county-level per capita disposable income for rural residents declined, coinciding with the rapid expansion of the digital economy. Whether this reduction in inequality was driven by digital economic development itself or by changes in how digital development affects income dispersion remains an open question. The RIF-OB decomposition proposed by Firpo et al. (2018) provides a useful framework for answering it.

Taking changes in the Gini coefficient as an example, the Gini of county-level per capita disposable income for rural residents declined from 0.201 in 2014 to 0.190 in 2018. In the RIF-OB decomposition, the endowment effect captures the contribution of changes in explanatory variables between 2014 and 2018, and the coefficient effect reflects changes in the impact of these variables on income inequality over time. Our regression results show that both effects contributed to the observed reduction in income inequality. Focusing on the endowment effect, neither e-commerce nor digital finance played a significant role, indicating that the decline in income inequality was not driven by changes in their development levels. In contrast, the coefficient effects were negative for all interaction terms between digital finance and the demonstration-county policy. Compared to 2014, the complementarities between digital finance and e-commerce contributed more strongly to narrowing income inequality in 2018. A plausible explanation is the increasing inclusiveness of both digital finance and e-commerce over time. In practice, as digital financial service providers deepened their involvement in rural revitalization, integrating with local e-commerce activities emerged as a more effective and mature model for boosting incomes and reducing disparities. From a dynamic perspective, these results suggest that the interaction between digital finance and e-commerce played an important role in reducing rural income inequality.

TABLE 3. Decomposing Changes in the Gini Coefficient over Time

2018 Gini coefficient (RIF)	2014 Gini coefficient (RIF)	Total change	Endowment effect	Coefficient effect
0.190***	0.201***	-0.0104*	-0.00278	-0.00764
(0.00422)	(0.00409)	(0.00588)	(0.0571)	(0.0573)
Decomposition target: 2018 Gini coefficient − 2014 Gini coefficient	Dimensions of the digital finance index used as explanatory variables			
	Overall Index	Coverage	Usage	Credit
Endowment effect				
Pilot county policy	-0.000429	-0.000131	-0.000617	-0.00111
	(0.00121)	(0.000768)	(0.000934)	(0.000889)
Digital finance index	-0.00195	-0.00835	0.00170	-0.000506
	(0.00414)	(0.00528)	(0.00166)	(0.00234)
Pilot county × Digital finance	-0.000595	-0.000346	0.000296	0.00150
	(0.00172)	(0.00270)	(0.000498)	(0.00170)

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Table3 Continued

Coefficient effect				
Pilot county policy	0.0578*	0.0602***	0.00685	-0.0256
	(0.0349)	(0.0228)	(0.0382)	(0.0623)
Digital finance index	0.792***	0.961***	0.323***	0.0516
	(0.131)	(0.117)	(0.102)	(0.114)
Pilot county × Digital finance	-0.0828***	-0.0490***	-0.0663***	-0.0902**
	(0.0142)	(0.00733)	(0.0183)	(0.0365)

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the county level are reported in parentheses. All regressions control for the full set of baseline covariates.

5.3.2 County-level heterogeneity

County-level endowments play an important role in shaping farmers' income. Given China's uneven and unbalanced regional development, natural differences in local endowments generate substantial income disparities across regions. If e-commerce and digital finance can compensate for disadvantaged endowments, or operate more efficiently given local conditions, their income effects may be stronger in low-income areas, providing a potential explanation for the results in Table 2. Existing studies have identified urbanization (Song and Xiao, 2005), agricultural mechanization (Zhou et al., 2016), and access to rural financial services (Zhu et al., 2007) as key county-level endowment characteristics affecting farmers' income. Accordingly, we classify all sample counties along these three dimensions, with clear income differences between the two groups within each dimension. Following Beck et al. (2010), we then construct time-invariant county characteristics using pre-policy data and include their interactions with digital finance and e-commerce in the regression. These results show that the complementarities between digital finance and the demonstration-county policy had stronger income effects in counties with a higher concentration of rural labor, weaker traditional financial development, and lower levels of agricultural mechanization.

5.3.3 The joint effects of e-commerce and digital finance on household labor income and labor allocation

With rising urbanization, nonfarm employment has expanded and wage income has become the main source of rural household income in China. We thus also examined how the interaction between e-commerce and digital finance affected different types of labor income. These results show that their interaction significantly increased both wage and self-employment income. A 100-point increase in the digital finance index raised the income effect of the demonstration policy by 6.12 percent for wage income and 3.6 percent for self-employment income. Although wage income inequality was unaffected, inequality in self-employment income declined, consistent with reduced financing constraints. In addition, the interaction significantly promoted local employment, suggesting that e-commerce and digital finance encourage labor to engage in local work and entrepreneurship.

6. Conclusion and Policy Implications

This paper studies how the joint development of e-commerce and digital finance shaped common prosperity in rural China. We find that their interaction significantly increased farmers'

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per capita disposable income and improved income distribution, as reflected in declines in the Gini coefficient, quantile gaps, and variance-based measures of inequality over our sample period. The inequality-reducing effect strengthened over time, consistent with the growing inclusiveness of digital finance and e-commerce. Heterogeneity analysis furthered showed that these effects were more pronounced in low-income counties, where the interaction both leveraged labor-intensive advantages and offsets constraints associated with weak traditional finance and low agricultural mechanization. At the household level, the interaction promoted local employment, raised both wage and self-employment income, and reduced inequality within self-employment income.

These findings have several policy implications. First, we recommend strengthening data-sharing mechanisms between inclusive finance institutions and e-commerce platforms. Consistent with the State Council's Guidelines on Promoting High-Quality Development of Inclusive Finance, policies should encourage data sharing between financial institutions and e-commerce platforms. Transaction data from e-commerce platforms can support alternative credit assessment for rural entrepreneurs by enabling integrated credit scoring that combines transaction records with traditional credit information, dynamic risk monitoring based on real-time data, and standardized data-sharing protocols with clear rules on data use and privacy protection. Such cooperation can help address the challenges in rural credit assessment while expanding access to finance for rural groups underserved by conventional credit systems, thereby reducing rural financial exclusion.

Second, we recommend promoting coordinated development between inclusive finance and rural e-commerce. Consistent with the Digital Rural Development Strategy Outline (2019)[9], policies should strengthen financial support for rural e-commerce by linking e-commerce programs with local specialty industries, expanding tailored products such as order- and inventory-based financing, and adopting data-driven, differentiated credit terms. This coordination may help to ease financing constraints and improve the effectiveness of financial services.

Third, policy design should account for regional heterogeneity. In labor-intensive regions, e-commerce skills training and support for local specialty industries can promote employment and entrepreneurship. In areas with weak financial infrastructure, inclusive financial products should be expanded and e-commerce data leveraged to develop alternative credit assessment mechanisms. In regions with low levels of agricultural mechanization, targeted credit programs, such as loans for machinery purchases, can help improve agricultural production conditions. Together, these measures can enhance the complementary roles of e-commerce and digital finance and improve the effectiveness of targeted rural support.

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